GLIOMA (BRAIN TUMOR) DETECTION USING OPTIMIZATION-BASED CLUSTERING TECHNIQUES IN MR BRAIN IMAGES

A SYNOPSIS

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1. INTRODUCTION

A group of cells that have developed abnormally either within or outside the brain is called a brain tumor. Malignant or benign brain tumors can be present. Whereas certain tumors emerge gradually, some quickly proliferate. Only one-third of brain tumors are cancerous. Once the tumors grow large enough to exert pressure on nearby nerves, tissues, and blood vessels, they may still have an impact on brain activity regardless of whether they aren't actually malignant [1-2]. Brain tumors are referred to as primary tumors. Tumors that originated in a different region of the body but have migrated to the brain are known as secondary tumors or metastatic tumors [3-4].

About 85,000 Americans are given a brain tumor diagnosis each year. Of the tumors, about 60,000 are benign and about 25,000 are malignant. Brain tumors are more prevalent in men compared to women. Despite the fact that they may occur at any stage of life, older people experience them the most frequently. Brain tumors are the leading contributing factor to cancer-related fatalities in children below the age of 14 [5].

According to doctors, unidentified causes account for the majority of brain cancer cases. A tumor can develop when brain cells start expanding beyond control due to changes in genetics or anomalies. The only known environmental cause for brain tumors is exposure to high doses of radiation from X-rays or prior cancer treatment. Some genetic illnesses, which usually ensue, result in brain tumors [6].

Along with an extensive medical record and medical investigations, the diagnosis of a brain tumor may be made using various imaging methods including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Magnetic Resonance Angiography (MRA), and cerebral angiography. The technique of extracting regions of interest from 3D image data, such as MRI or CT scans, is known as medical image segmentation. One of the main benefits of segmenting medical images is that identifying and separating merely required portions, it enables more precise anatomical data processing. Additionally,

segmentation allows for the separation of various tissues, such as bone and soft tissues, and excludes any undesirable information from the image, such as air. The segmentation process can be time-consuming, but quick advances in deep learning are making tasks possible. Researchers as well as practitioners can create a variety of segmented images for additional analysis when employed in association with different optimization algorithms.

Clinical image processing is used by technicians, doctors, and radiographers to fully understand the anatomy of their patients. It has recently evolved into one of the most useful medical technology instruments. Grey matter, white matter, and cerebrospinal fluid are the different tissue types that comprise the brain. It is possible to manually, somewhat automatically, or fully automatically isolate the required object or organ from a 2D or 3D medical image using the technique known as medical image segmentation, also referred to as natural image segmentation.

Finding the locations and extent of active tumorous tissue, necrotic tissue, and edema are the goals of tumor segmentation. This is accomplished by identifying aberrant areas in tissue and comparing it to tissue that is healthy.

Tumor segmentation is crucial for early detection and treatment planning. Due to advancements in deep learning, segmentation quality has significantly improved recently as compared to earlier approaches. In this thesis, we employ this technique to train feature hierarchies that take data from a variety of MRI modalities and are especially suited to the goal of tumor segmentation.

By assigning particular pixels to a cluster with the same characteristics, the clustering approach can be used to extract data in order to build clusters. Fuzzy C-means (FCM) and Fuzzy K-means (FKM) are the two clustering techniques that are most frequently used in image segmentation. In this thesis, the two different optimization methods namely, Social Spider Optimization (SSO) and Elephant Herding Optimization (EHO) are employed to obtain the

optimized cluster results. SSO is a population-based heuristic that mimics the cooperation of the social spider [7].

EHO method is a very effective optimization tool based on the behavior of elephants that performs better than SSO based on the behavior of spiders. The necessity for the EHO algorithm has considerably broadened as a result of artificial intelligence, and computerized decision-making techniques have proliferated across essentially every sector.

Clustering can be done using modified FCM techniques like Fast and Robust FCM (FRFCM), Fuzzy Clustering by Local Approximation of Memberships (FLAME) and Entropy based Fuzzy C- means clustering (EnFCM) [8]. This thesis presented a hybrid strategy for automatic tumor segmentation that combines the above-mentioned modified FCM methodologies with SSO and EHO to produce optimal segmentation results.

This thesis has a strong emphasis on experimental study using the MICCAI brain tumor (BRATS) challenge datasets from 2013, 2015, 2018, 2019, 2020, and 2021. This allows us to forthrightly and quantitatively compare the proposed algorithm to a wide range of other approaches and exhibit its superiority.

The dissected outcomes of the suggested method are compared with their corresponding BraTS ground truth images. By contrasting the algorithms' results with those of physicians and real-world images, the findings are shown to be accurate [9]. For the purpose of determining the algorithms' competence, the performance metric values for each suggested algorithm are evaluated.

The performance metrics including mean-squared-error (MSE), peak-signal-to-noise-ratio (PSNR), Tanimoto-co-efficient-index (TC), Dice-Score (DS) and computational time (T) are assessed during dissection process and was compared with the conventional researchers’ outcomes. In order to employ this optimization method for prompt diagnosis, a thorough investigation is provided to both academics and practitioners [10].

2. LITERATURE REVIEW

For a more comprehensive understanding, this section presents the results and evaluations of several newly developed image segmentation and optimization techniques that have been presented out. Deep learning-based brain tumour segmentation is a topic of interest in the medical imaging and machine learning environments. From 2012 onwards, the Multimodal Brain Tumor Segmentation challenge, in conjunction with medical image computing and computer-assisted intervention (MICCAI), has greatly contributed to the development of deep learning-based brain tumour segmentation techniques. Over a few most newly enacted techniques based on DL is reviewed below.

Jiang et al. developed an automated segmentation method for tumour dissection from MR brain images using the SwinBTS algorithm, which includes CNN, encoder-decoder, and transformer [11]. The developed algorithm was evaluated on multiple BraTS challenge datasets, yielding dice score values of 74.43% (BraTS 2019), 77.36% (BraTS 2020), and 83.21% (BraTS 2021).

Hu et al. proposed the mutual ensemble learning model for earlier and more accurate assessment of anomalies in brain MRI, as well as for minimising generalisation errors throughout training and testing [12]. The proposed method's efficiency was affirmed by testing it on the BraTS 2015 and 2018 datasets, which produced better results than conventional methodologies.

Ullah et al. used a multiscale residual attention strategy with U-Net to precisely separate tumour from brain MRI [13]. Three successive images are used as an input for retain the contextual data, and multiscale learning is used as sequence, allowing by utilising the interest of adaptive region/area method to reliably separate the tissues. When tested on the BraTS 2020 dataset, the DC value obtained was 90.18%.

Tumor dissection method that comprises super voxel feature extraction and MetricUNet was suggested by Liu et al. and was validated using BraTS 2019 dataset [14]. The contextual data about the images are assessed by scale adaptive method and the features which defines the edges/borders are extracted using super voxel feature extraction strategy.

Fang and Wang devised a method to classify the oddities in multimodal images from multiple perspectives. Traditional approaches were failed to demonstrate their sturdiness when evaluating multimodal images from multiple angles [15]. Here, the DenseNet fused the extracted features, which are classified as low, middle, and high level and contain limited and greater receptive regions. The incorporation of this method aids in enhancing the resiliency of the developed method and limiting the loss of boundary data. All the features are combined, and the resulting image accurately depicts the tumor structure.

Ilhan et al. proposed a histogram-based nonparametric anomaly identification approach to pinpoint the tumour location, along with U-Net, it precisely enhance the tumorous portion [16]. The inclusion of U-Net in this automated system improves and segments the visual appearance of the tumour. The proposed method was examined on the BraTS 2012, 2019, and 2020 datasets and achieved 94%, 85%, and 88% DC, respectively.

Nyo et al. developed an automated technique for tumor segmentation from brain MRI using Otsu's thresholding method [17]. The noises developed by the radiations in the MR images are diminished by incorporating median filter. The Otsu's thresholding method is applied on noise removed filtered images to segment the tumor and non-tumor sections. The derived process was validated by BraTS 2015 which accomplished 68.7% accuracy.

Bacanin et al. suggested a metaheuristic approach to categorise glioma brain tumour grades using diverse sources, the normal brain tumour images are taken from the IXI dataset, and the glioma MRI with grades I, II, III, and IV are taken from the cancer imaging archive [18]. For classification, the enhanced Firefly optimization method and CNN are utilised. In the experiment with the first dataset, the proposed methods outperformed CNN + GA by 2.4%, while in the experiment with the second dataset, the proposed method outperformed CNN + GA by 2.3%.

Thilagaraj et al. proposed a CNN based on an artificial fish school method using breast cancer images from cancer imaging archives [19]. The artificial fish school optimization technique helps to reduce the error rate and improve

performance efficiency by choosing the number of epochs and training images for the Deep CNN. Preprocessing is accomplished using the wiener filter. The provided model compares the cuckoo search algorithm with the existing radial basis neural network technique to achieve the desired result in terms of sensitivity, accuracy, specificity, F1 score, and recall.

Hooda et al. studied the classification of brain MRI using the fuzzy-gravitational search algorithm (GSA) using four benchmark datasets from the UC Irvine repository [20]. The results are compared with GSA and current research on brain image segmentation techniques for both real-world and hypothetical databases based on Dice Coefficient values. The results demonstrate that the Fuzzy-GSA methodology achieves the highest quality clustering over the selected datasets when compared to various alternative clustering algorithms.

Chen et al. suggested an ensemble multi strategy-driven shuffling frog leaping algorithm with horizontal and vertical crossover search for multi-threshold picture segmentation using Berkeley classification datasets (HVSFLA) [21]. On cases with breast invasive ductal carcinoma, this algorithm was used. The experimental results demonstrate that the proposed HVSFLA performs better than a wide range of comparable competitors, and as a result, it holds great promise for application in medical image segmentation.

Wang et al. suggested an enhanced pulse coupled neural network for segmenting medical images using multiple hybrid features grey wolf optimizer [22]. To confirm the viability of the suggested method, FLAIR and T1C brain MRIs are used as two different imaging modalities. The experimental findings show that in terms of subjective vision and objective evaluation indicators, the proposed method performs better than the traditional methods.

Problems encountered with the above segmentation algorithms include (i) strong perception of noise and artifacts; (ii) higher processing time; (iii) lower accuracy in noisy images; (iv) loss of WM, GM, and CSF parts during segmentation; (v) lack of robustness in optimization; and (vi) cluster overlapping.

Despite all of the potential and advantageous applications of deep learning approaches, some areas remain to be explored. This research concentrates on unexplored options in the use of deep learning, and it has been very influential in the outcome of several meta-heuristic algorithms using EHO optimization and modified forms of fuzzy clustering for complex processes such as tumour region recognition and tissue segmentation in MR brain images. In this analysis, significant progress was made, and the outcomes were substantiated using all available performance measures.

3. OBJECTIVES

The main objectives of the research are as follows:

I. To segment the tumour portions in an MR brain image using a modified version of the novel EHO algorithm.
II. To reduce the overall convergence computation cost by using the fewest possible control parameters.
III. To develop a fully automatic system with dual metaheuristic optimization techniques to segment brain MRI with a higher success rate than the single optimization algorithm.
IV. To address the exploitation and exploration limitations confronted by the optimization algorithms during search operations with suitable modifications to their standard operations and,
V. To dissect the infectious region from MRI using the self-accommodative EHO optimization algorithm based on modified FCM.

4. RESEARCH PROBLEM

MRI can aid in the diagnosis of a brain tumour; however, if the tumour is engrossed by edema in the scan, radiologists may struggle to pinpoint the exact location of the tumour because it is obscured by voluminous tissues and edema. A standard image analysis method available in an imaging centre cannot even segment healthy tissue portions. In these kinds of situations, the diagnosis will be prolonged, and if the procedure is also assertive, the patient’s survival period

may decline. Furthermore, as the dataset to be diagnosed increases, the radiologist's task will become more erratic. So, there is a need for a fully automatic and efficient algorithm to segment tumour, tissue, and edema regions in all kinds of MRI, such as T1-W, T2-W, and FLAIR.

5. CONTRIBUTIONS

5.1 Glioma Detection Using Elephant Herding Optimization (EHO)-based Fuzzy Clustering by Local Approximation of Memberships (FLAME) Clustering in MR Brain Images

Fuzzy clustering is a type of cluster analysis in which data points can pertain to more than one group or cluster. Clustering is an unsupervised method of machine learning that splits data points into clusters according to the similarities among datapoints. Fuzzy clustering employs least-squares remedies to determine the best position for any data point. This optimal position could be somewhere in the probability space among two or more groups/clusters. The most common clustering method is fuzzy C-means (FCM). FCM has several drawbacks as it underperforms on data sets with unevenly cluster sizes, and it is vulnerable to noise and outliers. Several variations of FCM algorithms have been developed to overcome these FCM downfalls.

Fuzzy Clustering by Local Approximation of Memberships (FLAME) method describes clusters in complex sections of an image and allocates clusters relying on neighbouring pixel associations. An important factor of this method is the use of the relationship among neighbouring pixels in the higher dimensional space to constrain the membership value of adjacent pixels in the fuzzy membership space. FLAME categorization has variety of advantages, including the ability to discern non - linearities and non-globular clusters, the automatic characterization of cluster number, cluster outlier recognition, and the recognition of pixels that have not been assigned to any cluster. Internally, the clusters seem to be more homogeneous and diverse from one another, allowing for better pixel separation.

The growing complexity of serious challenges makes conventional methods of solving them nearly impossible. Advanced meta - heuristic optimization techniques, on the contrary, can produce feasible solution within a sensible amount of time even if they're unable to deliver clear results. Numerous sorts of metaheuristic methods have been suggested and effectively implemented to deal with a variety of real-life problems in recent years. Swarm-based techniques are one among the most delegate and extensively utilised meta - heuristic optimization frameworks. Its motivation comes from animal social behaviour.

Elephant Herding Optimization (EHO), a new category of swarm-based metaheuristic technique influenced by elephant herding behaviour, is proposed to address optimization tasks. The natural behaviour of elephant herding is idealised as separating operator and clan updating operator. In this method, each elephant enforces a clan updating operator to notify its position based on the responding clan's present position and matriarch. Following that, the worst elephant is altered by a separating operator. The benefit of the EHO technique over numerous state-of-the-art (SOTA) meta-heuristic methods in determining the best solution to several optimization problems has piqued the interest of researchers.

Figure 1 shows the recommended method in this paper integrates Fuzzy Clustering by Local Approximation of Memberships (FLAME) for clustering and Elephant Herding Optimization to achieve the best outcomes in segmenting the tumor from MR images. Several experiments are conducted to evaluate EHO's effectiveness, and the findings demonstrate that EHO could indeed find much better solutions to most benchmark issues than other methodologies.

Figure 2 shows the proposed approach has been thoroughly tested using BraTS datasets. In contrast to current state-of-the-art techniques, the suggested method accomplished superior results for tumour segmentation.

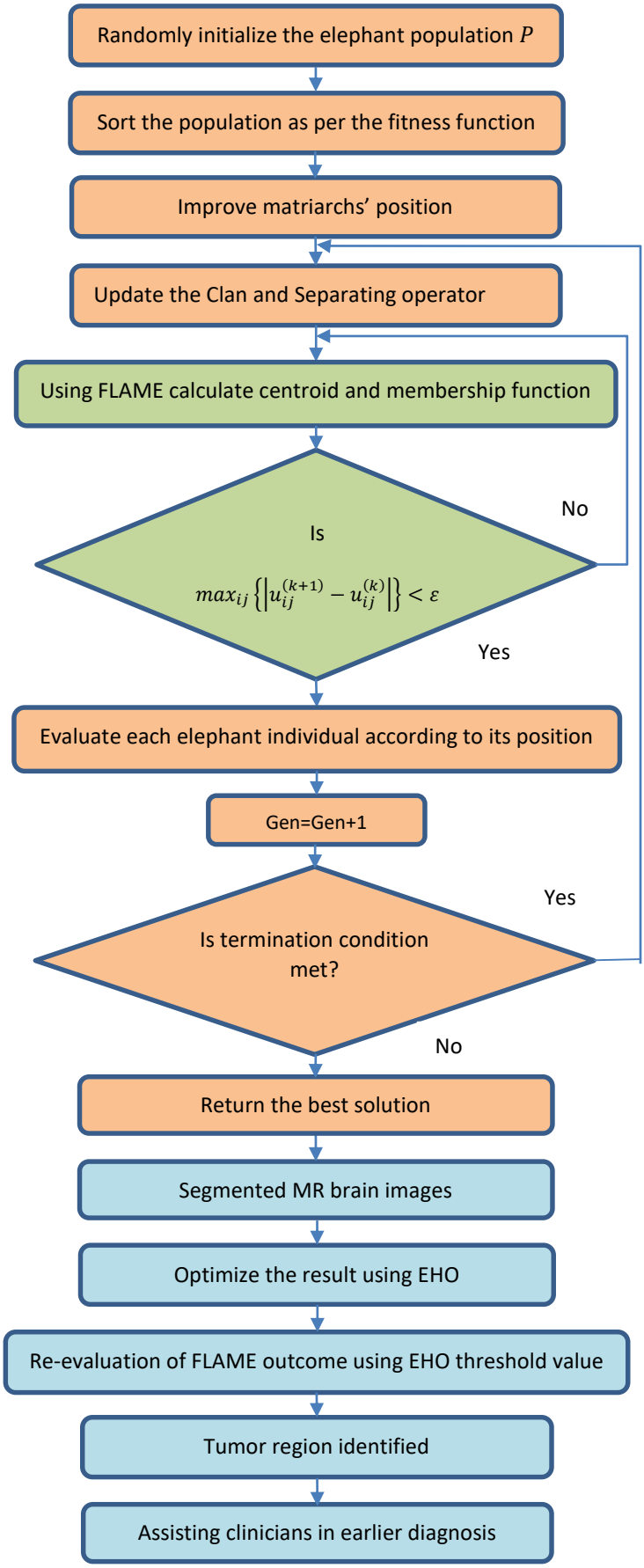


Figure 1. Workflow for EHO-FLAME Technique

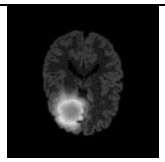
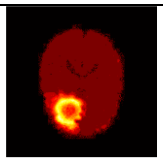
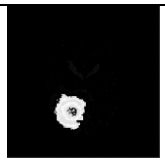
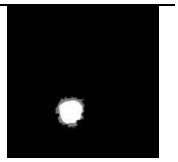
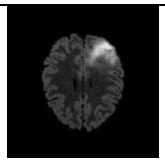
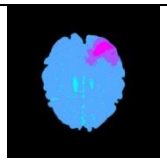
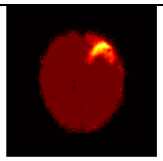
Image Type	Input Image	FLAME	EHO-FLAME	Identified Tumor Region	Brats ground truth Image
BraTS 2013 LG FLAIR					
BraTS 2013 LG FLAIR					

Figure 2. Segmentation outcomes of EHO-FLAME algorithm

The average performance values achieved for segmenting the tumor from various BraTS datasets are described as follows: The attained average computational time, MSE, PSNR, TC and DS are 23.3775 Sec, 0.213, 54.9669 dB, 54.6148 % and 84.053 %, respectively.

5.2 Multimodal MR Brain Image Segmentation using Hybrid Optimization Techniques for Earlier Prognosis of Tumor

FCM outperforms hard clustering because it tolerates uncertainty better and preserves more existing image data. FCM is effective for images with normal background, but it falls down to dissect objects with noise because it solely perceives gray level details leaving spatial data into account. This could be avoided by incorporating spatial information in the objective function.

Experts have been drawn to swarm intelligence (SI) algorithms because of their robust and effective results in addressing optimization problems. The Social Spider Optimization (SSO) model considers the search space to be a communal spider web, with each candidate solution representing a spider.

Each spider is assigned a weight determined by the fitness value of the solution it represents. The method employs two distinct search sets of evolutionary operators to replicate the various cooperative behaviours presumed in the colony. The method was created to address a global non - linear optimization difficulties.

This study combines the FRFCM and SSO to create an automated hybrid algorithm for recognizing and extracting glioma in MR brain images. The recommended FRFRCM-SSO metaheuristic algorithm forms the better clusters and trying to balance the exploration and exploitation challenge and offers the most efficient solutions for optimization problems. Figure 3 depicts the wokflow of SSO algorithm.

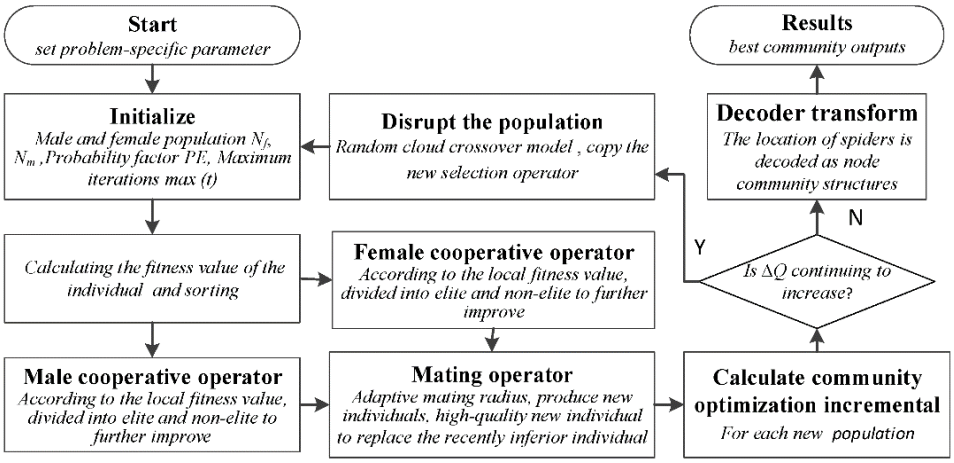

Start
set problem-specific parameter
Initialize
Male and female population N_f, N_m ,Probability factor PF, Maximum iterations max (t)
Calculating the fitness value of the individual and sorting
Female cooperative operator
According to the local fitness value, divided into elite and non-elite to further improve
Male cooperative operator
According to the local fitness value, divided into elite and non-elite to further improve
Mating operator
Adaptive mating radius, produce new individuals, high-quality new individual to replace the recently inferior individual
Disrupt the population
Random cloud crossover model , copy the new selection operator
Calculate community optimization incremental
For each new population
Is ΔQ continuing to increase?
Y
N
Decoder transform
The location of spiders is decoded as node community structures
Results
best community outputs

Figure 3. SSO Algorithm

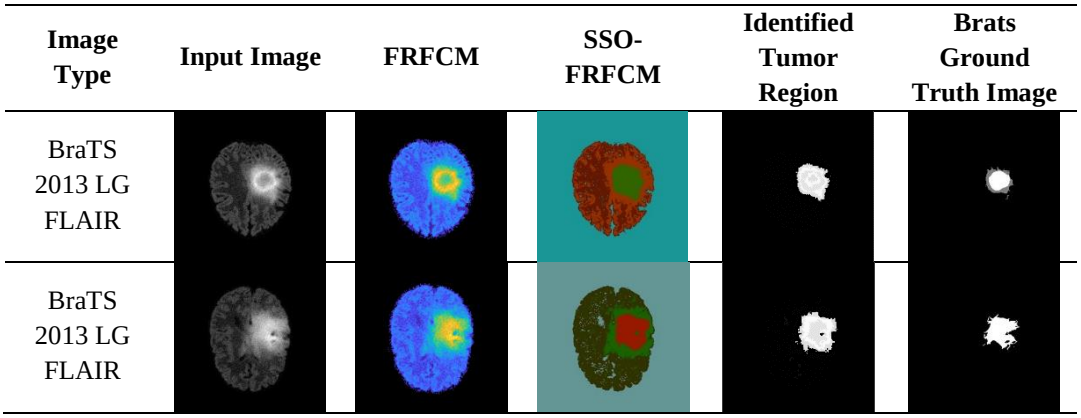


Figure 4. Glioma tumor segmentation using FRFCM-SSO method

Figure 4 displays the glioma tumor segmentation using FRFCM-SSO method. The average performance values achieved for segmenting the tumor from various BraTS datasets are described as follows: The attained average computational time, MSE, PSNR, TC and DS are 22.9 Sec, 0.3044, 53.4341 dB, 57.4962 % and 77.8089 %, respectively.

5.3 Enhancing MRI-based Early Brain Tumor Detection with Entropy-driven Fuzzy C-Means and Elephant Herding Optimization

The EnFCM algorithm, which uses entropy-based fuzzy clustering, operates using a similarity threshold. In contrast to FCM, EnFCM uses actual cluster centres that are selected from the data points. The quantity and calibre of clusters can be altered by altering this variable. Here, the data points' entropy values are initially estimated, and the data point with the lowest entropy value is chosen as the cluster centre. The data points are grouped according to a threshold level of similarity in this iterative technique. Outliers are data points that are not chosen for inclusion in any of the clusters. The EnFCM helps generate better clusters with a maximum of related pixels.

To recognize and extract the cancer and non-tumor sections from MR brain pictures, a hybrid automated system has been created. This technique combines EnFCM for clustering operations and EHO for improved optimization. On the dataset from the Brats challenge, the effectiveness of the generated algorithm was examined. The segmented results are contrasted with their respective in-repository ground truth images. To determine the effectiveness of the proposed strategy, performance metrics are compared to the results of cutting-edge methodologies.

Figure 5 shows the newly developed EHO-EnFCM approach discovered and fragmented the tumour region visible in the MR images, aiding in an earlier identification. The efficacy of the dissection outcomes of the developed technique is validated by comparing it with their respective ground truth images. Figure 6 displays the results of segmenting BraTS MR images using the EHO-EnFCM method.

The following is a description of the mean performance values obtained for segmenting the tumour from multiple BraTS datasets: The attained average computational time, MSE, PSNR, TC and DS are 26.57 Sec, 0.29, 53.57 dB, 57.76 % and 80.07 %, respectively.

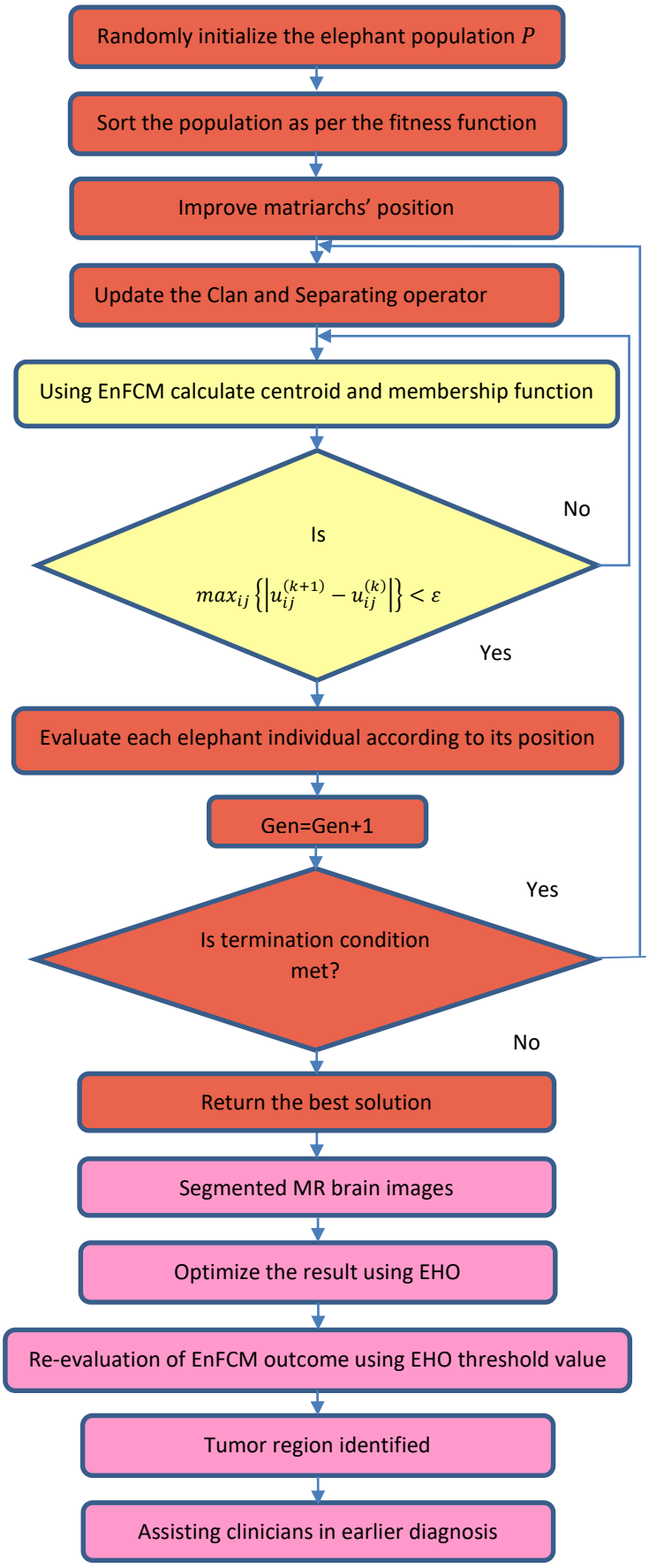

Randomly initialize the elephant population P
Sort the population as per the fitness function
Improve matriarchs' position
Update the Clan and Separating operator
Using EnFCM calculate centroid and membership function
Is
$max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$
No
Yes
Evaluate each elephant individual according to its position
Gen=Gen+1
Is termination condition met?
Yes
No
Return the best solution
Segmented MR brain images
Optimize the result using EHO
Re-evaluation of EnFCM outcome using EHO threshold value
Tumor region identified
Assisting clinicians in earlier diagnosis

Figure 5. Workflow for EHO-EnFCM Technique

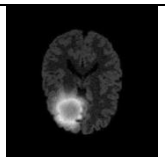
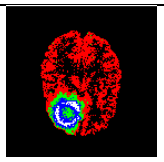
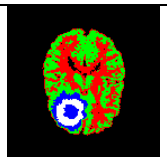
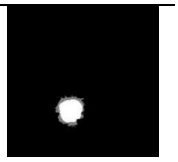
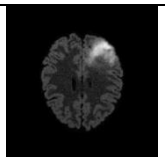
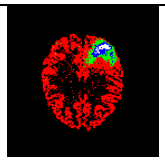
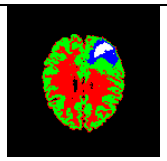
Image Type	Input Image	EnFCM	EHO-EnFCM	Identified Tumor Region	Brats ground truth Image
BraTS 2013 LG FLAIR					
BraTS 2013 LG FLAIR					

Figure 6. Glioma tumor segmentation using EHO-EnFCM method

VI. CONCLUSION

The clusters' local approximations of the pixels are recognised, and similarities between them are determined. Elephant herding habit imitates and helps generate clusters of like pixels that resemble the development of a clan. The recommended approach assists in processing brain MR images that are complicated by issues including noise invasion, intensity inhomogeneity, and atypical tumours in a variety of dimensions, forms, and positions. The tumor dissected images are verified with the corresponding ground truth images to determine the resemblance. As a result, the innovative EHO and FLAME approach produces a value of 84.053% as a dice score.

On images with single or numerous tumours and varied forms and spots, the proposed EHO-FLAME approach performed exceptionally well. These logical conclusions might open the door to precise disease identification in patients. The suggested approach could be incorporated into therapeutic procedures to allow accurate estimation of strangeness throughout therapy, leading to faster diagnosis. The segmented results unambiguously demonstrate that cancers are broken down in a respectable amount of time and that by maximizing the variable, this process might speed up even more. The future direction of the research aims to improve PSNR, TC, and DS while reducing MSE and time for computation.

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